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Automatic description of the Gulf Stream from IR images using neural networks

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ABSTRACT

A system under development for automated interpretation of oceanographic satellite images includes a Gulf Stream description module which uses a neural network, which produces coefficients of an empirical orthogonal function (EOF) series representation of the Gulf Stream directly from processed satellite imagery. The Gulf Stream module consists of the EOF software and the neural network, with input from an innovative edge detector.

The Gulf Stream is the swiftest and most energetic current in the north Atlantic, and meanders with a broad spectrum of variability on several spatial and temporal scales. Satellite observations provide a means to observe the Gulf Stream's shape, although clouds in IR imagery and other types of "noise" complicate interpretation. The Gulf Stream shape at any time may be represented as a series of complex EOFs (CEOFs), i. e., principal components, which can be truncated after a relatively small number of terms (10) and still describe Gulf Stream shapes well (to within 10 km). These modes can be optimized from initial values with as few as 21 fixes on the position of the Gulf Stream axis, using least-squares estimation. The CEOFs interpolate between spatially intermittent observations of portions of the Gulf Stream, as might come from IR imagery with partial cloud cover.

The study described here tested whether a credible Gulf Stream can be produced using a neural network (simulated in software) that has inputs derived from imagery, and has CEOF coefficients as outputs. To demonstrate feasibility we considered it sufficient to define the values of the first three complex mode coefficients, which account for more than 97% of the Gulf Stream's position variance. Two data sets were used for training and testing: Gulf Stream analyses from NOARL's GEOSAT Ocean Applications Program (GOAP), and edge images produced from IR imagery by a NOARL-developed algorithm.

In the first part of the study the input consisted of 132 latitude-longitude pairs that represent one Gulf Stream. The learning algorithm is back propagation; convergence is achieved with 100,000 iterations through the training set with the learning coefficient set to 0.9 and the momentum coefficient set to 0.6. The neural network has one hidden layer with 10 nodes. The output layer has 6 nodes, giving the real and imaginary parts of each of the three CEOF mode coefficients. Training using the GOAP data set produces outputs that have correlation coefficients with the correct mode coefficients averaging over 0.98.

The next part of the study used a network with a 50 x 50 grid (simulating pixel input) of input nodes, one hidden layer of 40 nodes, and 6 output nodes. Again, learning was by back

propagation. The training set consisted of 77 of the 86 GOAP data sets, with 9 randomly chosen sets held back as test data. The network converged after 150,000 passes through the test data set, with results of comparable accuracy to those obtained with the first network. Processing to produce three complex mode coefficients from 50 x 50 gridded input took less than 1 second on a 20 MHz PC.

The grid-input network applied to the 9 GOAP test cases achieves agreement with a correlation coefficient averaging 0.97. The results are moderately good for the noisy edge imagery, also. The coefficients have reasonable values, the correlation coefficient between the network and actual coefficients averages 0.69, and the resulting reconstructed Gulf Stream is within 100 km of the actual Gulf Stream over most of its length. This is notable because the resolution of the 50 x 50 grid is 50 km.

The studies performed so far demonstrate feasibility. The next phase of work is directed toward making the system operationally useful.

1. INTRODUCTION

This work is part of an effort to develop and demonstrate techniques for automated interpretation of satellite data for ocean and ice applications. Generation of oceanographic products by conventional manual means requires much labor and very high skill levels, both of which are difficult to realize in an operational environment. The satellite oceanography image understanding problem is difficult because the features are naturally time-varying, there are no straightforward mathematical models of their shapes, and interference by cloud cover and other effects is a frequent problem. To address these difficulties, the technical issues the project considers are image segmentation (simplification), feature labeling (assignment of oceanographic identity to image features), feature aggregation (formation of Gulf Stream north wall, eddies, etc.), and mesoscale extrapolation (to deal with data gaps). This paper describes an innovative approach to the feature labeling and feature aggregation portions of the automated Gulf Stream detection problem.

Satellite imagery, by its capability for synoptic coverage of large areas, is a useful complement to traditional in situ oceanographic measurements. Hawkins, Phoebus, and May[1] discuss the assimilation of satellite data along with other types of information to produce a superior description of oceanic parameters. During the past few decades, new observations have begun to identify a phenomenon that appears to be intimately linked physically to the ocean's general circulation, and even to dominate the circulation energetically in many regions. This phenomenon is comprised of slow, medium-sized fluctuations in the circulation itself. This "mesoscale" variability can take several forms, such as meandering of the Gulf Stream, large ring vortices that are snapped off from the currents during intense meandering events, and the mid-ocean eddies.

The sea surface is teeming with thermal structure detectable by satellite infrared (IR) sensors. Present sensors are capable of 1 km horizontal resolution with 0.5°C accuracy under cloud-free conditions. The Gulf Stream and its rings contribute to the surface thermal expressions observed by satellite. Specifically, the Gulf Stream is a continuous feature in the north Atlantic Ocean whose surface thermal expression consists of sea surface temperature gradients between the longitudes 75°W and 40°W. Images can be produced in which pixels have been identified that are associated with high horizontal gradients and thus are candidates for the Gulf Stream edge. The problem, then, is to discard some of these high gradient edges and connect the rest into a continuous Gulf Stream. A mathematical description of a continuous Gulf Stream with realistic meanders has been

developed. The innovative step described in this paper is the use of the new technology of neural networks to connect the gradients of IR imagery to the mathematical description of a continuous Gulf Stream. The technique has the potential to apply the great speed and quantitative effectiveness of artificial intelligence technology to the identification of oceanographic features from remotely sensed imagery. This, in turn, offers the benefit of more effective use of the U. S. Navy staff assigned to the task in the Fleet.

The emerging capabilities of neural networks to reduce noisy imagery to meaningful information in a fast, highly parallel fashion presents an opportunity to solve longstanding problems in satellite data analysis. A neural network implemented in either software or hardware greatly decreases the need for a human operator to examine the IR imagery, since the network operates directly on the data to produce probable Gulf Stream points. This computer implementation yields another immediate benefit--the processing begins as soon as the satellite data are acquired instead of waiting for a human expert to analyze the data. The necessity for specialized shore-based display equipment and interactive software are also diminished because the network operates on the digital data directly as it is received from the satellite or automatically processed by existing edge detection algorithms.

In addition to countering the deficiencies outlined above, a neural network capable of analyzing IR imagery opens up new possibilities in the U. S. Navy's use of satellite data. The capability to analyze satellite imagery without the use of an expert and extensive workstation introduces the possibility of onboard analysis of data. This enables properly equipped vessels to make critical decisions based on the latest information in near-real-time without the delays of a system dependent on shore-based facilities.

During the early 1990s the U. S. Navy will face an unprecedented wealth of new remotely sensed oceanographic data available from both U. S. (e. g., TOPEX/Poseidon, Spinsat) and foreign (European ERS-1, Japanese ERS-1) satellites. Present-day satellites will continue to supply oceanographic data into the forseeable future. The sheer volume of data from these satellites will be overwhelming to analysts, and anticipated manpower reductions will dictate a need for greater automation. This data volume increase will coincide with the deployment of the third version of the Tactical Environmental Support System (TESS (3)), a capable environmental information system which will extend satellite data processing capability to approximately 70 U. S. Navy ships and shore facilities. Thus, the work described in this paper is coming along at the right time.

2. BACKGROUND

A useful numerical description of the Gulf Stream is one based on complex empirical orthogonal functions (CEOFs), the eigenvectors of an "expectation matrix." The expectation matrix is obtained by averaging a set of matrices each representing the correlation properties of an individual vector, in our case a vector that describes the instantaneous position of the Gulf Stream. This formulation and its advantages for describing the Gulf Stream are described in detail by Carter.[2] To summarize that reference, a looping, contorted, but continuous Gulf Stream can be described by a vector of complex elements consisting of (latitude, longitude) pairs. That vector can be approximated well by a relatively small set of complex coefficients--when each coefficient is multiplied by a corresponding CEOF (principal component, eigenvector, or mode) that is fixed for all time. The resulting terms are a set of vectors which are added together to reproduce the original Gulf Stream vector. Speaking geometrically, the CEOFs constitute a set of basis vectors that span the space of all known Gulf Stream states (i. e., locations and shapes); an individual Gulf Stream state is produced by linear combinations of the basis set. Speaking figuratively, the CEOFs are the shapes of Gulf

Stream patterns and the coefficients are the orientations and sizes of the patterns. The power of the method derives from the fact that a partial sum, involving a relatively small number of CEOFs, may reproduce the Gulf Stream's shape with sufficient accuracy.

Mathematically, the Gulf Stream is defined by a complex vector **W** whose elements are:

$$W_j = x_j + i\, y_j \tag{1}$$

In this equation, x is the longitude and y is the latitude of a point on the Gulf Stream axis. This complex formulation allows the description of a contorted Gulf Stream which may curve back on itself, while a description in terms of y as a function of x, or vice versa, would have to deal with double-valued functions. The expectation matrix A is defined as the matrix with elements:

$$A_{ij} = \left\langle W_i W_j^* \right\rangle, \tag{2}$$

where * denotes the complex conjugate and < > is the expectation operator. A, which is generated from an ensemble of Gulf Stream axes, is Hermitian, so it has real eigenvalues (but complex eigenvectors). Given the eigenvectors E_k of A, and one particular realization, **W**, of the Gulf Stream, the complex mode coefficients associated with **W** may be found from:

$$C_k = E_k^H \mathbf{W}, \tag{3}$$

where the superscript H denotes the Hermitian conjugate. The coefficients allow the realization **W** of the Gulf Stream to be reconstructed using the expansion:

$$\mathbf{W} = \sum_{k=1}^{N} C_k E_k, \tag{4}$$

where N is the number of eigenvectors.

The eigenvectors of A form a complete set of orthogonal basis vectors. If the eigenvectors are sorted according to the size of the corresponding eigenvalues (k = 1 has the largest eigenvalue, etc.), then it is easily shown that the first eigenvector is the best fit in a least-squares sense to the "cloud" of points in the mathematical space in which each Gulf Stream (vector) defines one point. That is, the sum of squares of the total distances between the points and the "line" are a minimum. (This is analogous to what Duda and Hart call "eigenvector line fitting."[3]) So, the first eigenvector is aligned with the direction of maximum scatter (i. e., variance) of the points. Likewise, the second eigenvector "explains" the next largest amount of variance, etc. In fact, each eigenvalue is proportional to the amount of variance that a given eigenvector explains.[4] An immediate consequence of this is that, in practice, Eq. (4) may be truncated after a relatively small number of terms and still reconstruct a particular Gulf Stream with sufficient accuracy. Figure 1 illustrates the reconstruction of a convoluted Gulf Stream using the first 10 of 132 eigenvectors.

Many readers are familiar with normal mode analysis and have seen the above formulation in other contexts. Also, the reconstruction algorithm appears to fail when one does not have a complete description of a Gulf Stream (i. e., some of the elements of **W** are missing) because of cloud cover or some other form of interference. In this case, NOARL's software employs a gradient-search technique to perform a least-squares fit of the CEOF expansion to

the portions of the Gulf Stream which are observed. The coefficients found in a (recent) previous analysis are suitable initial estimates.[5]

This latter step is, itself, an innovative approach to providing a mathematical description of a realistic, continuous Gulf Stream from incomplete observational data. A further development involves the application of neural network technology. Neural networks have been emerging as a new, viable technology for image analysis and pattern recognition. There are several characteristics of neural networks that make them effective for analyzing large amounts of data rapidly and resistant to noise in the data. Neural networks are composed of many simple computational units that work in unison to process information. The network is not programmed in the traditional sense; rather, the weights that connect the neurons are "learned" by the network through repeated applications of input data for which the desired result is known. Thus, a network can be presented with an IR image or other input data, and it can process that data based on the information presented during training. The network is tolerant of noise since it has learned the salient features of an image during training, and the noise is in some sense averaged out.

NOARL has developed an edge-detection algorithm, the cluster-shade edge detector (CSED), to compute the position of sea-surface temperature (SST) gradient fronts in IR imagery.[6] That algorithm has several advantages for this application, compared to other, well-known edge detectors, such as the Sobel algorithm.[7] The immediate need is to identify the Gulf Stream among the fronts. Alternatively, we may say that the Gulf Stream is the pattern to be recognized in a CSED image, and other fronts constitute noise in that edge image. This paper describes an exploration of the capacity of neural networks to recognize the Gulf Stream pattern, as represented by CEOF coefficients, within the noise of an SST image processed by the CSED algorithm.

3. ISSUES IN NEURAL NETWORK PRODUCTION OF CEOF COEFFICIENTS

The basic question to be answered was whether a neural network can produce meaningful coefficients for CEOFs whose structures were not available to the network. That is, are the patterns represented by coefficients of CEOFs appropriate for neural network technology? To answer this question, it was necessary to consider several subquestions, or issues:

1. What constitutes an appropriate training set for the network?
2. What is the criterion for a meaningful CEOF coefficient?
3. What, if any, neural network training procedure is capable of producing meaningful coefficients for CEOFs from the chosen training set?
4. What is an appropriate configuration of nodes and layers to produce meaningful CEOF coefficients?
5. How sensitive to the configuration of hidden layers and nodes is the production of meaningful CEOF coefficients?

CEOFs computed by Molinelli and Flanigan[5] were expressed as vectors with elements every ten nautical miles downstream. Operational use would provide latitudes and longitudes of possible Gulf Stream locations derived from SST edge imagery that could not be associated a priori with distance downstream. Consideration of this fact led to the next issue:

6. Can input nodes representing positions on a latitude-longitude grid produce meaningful CEOF coefficients?

It was deemed necessary to resolve these issues before getting to details of noise discrimination, conditioning of input data, and increase in resolution and accuracy of the neural network output.

4. APPROACH

A simple approach was employed in investigating the above questions. That approach was to use a series of actual Gulf Stream representations produced between January 1986 and June 1987 to develop a neural network and test its capabilities. The Gulf Stream representations came from the "mesoscale products" of the GEOSAT Ocean Applications Program (GOAP),[8, 9] and were derived by a human analyst using not only IR SST imagery but also GEOSAT altimetric profiles. There are 86 Gulf Streams represented by latitude-longitude pairs at inflection points stored in computer files. This set of Gulf Streams constitutes the first candidate training set for the present study.

We used the CEOF software developed by Molinelli and Flanigan,[5] and started by deriving new CEOFs for the training data set. To demonstrate feasibility, we consider it sufficient to define the values of the first three mode coefficients. Together these modes account for more than 97% of the displacements of the Gulf Stream. Higher accuracy could be attempted in future work by using more modes.

A second candidate data set consisted of edge images produced using the CSED algorithm.[6] However, there are only a few dozen views of the sea surface clear enough to span the domain during the 18-month period spanned by the GOAP mesoscale product data set. Previous experience with neural network training led us to conclude that a substantially larger set of images would be required for training to converge in the presence of noise (other SST fronts) in these images. Nevertheless, we did obtain six warmest-pixel composite SST images[10] and the resulting edge images, as well as the nine individual SST images that contributed to the composites and their edge images. In all cases the edges were computed using the 16 x 16 pixel option of the CSED software[6] because the other options produced perceptibly more fine-grained noise. Even though the edge images could not be used as a training set, we did intend to use these images as test cases for the network's performance.

We chose the correlation between the coefficients produced by the neural network and the actual values produced by the CEOF software from the appropriate GOAP mesoscale product as a measure of how meaningful the set of CEOF coefficients generated by the neural network is. Specifically, we regarded the coefficients in a test case as meaningful if they are correlated with the actual values with a correlation coefficient of 0.8 or better. For cases in which there are too few pairs to compute correlation, we considered agreement of mode coefficients within 20% to be meaningful.

We used a commercial software package, Neuralworks, to establish which training procedure generates a network whose output best converges to the training set's actual coefficients. "Best," in this context, means fewest number of training steps and the smallest discrepancies between the network output and the training set coefficients. The input in this case was the 132 latitude-longitude pairs that define one Gulf Stream, i. e., 264 nodes. The output is a set of six nodes--real and imaginary parts of three CEOF coefficients. We also used the commercial software to vary the number of hidden layers and the number of nodes in those layers. Parameters of the learning algorithm, number of nodes, and scaling of input and output values are all modified empirically at this stage in order to achieve convergence.

The commercial software accesses only limited memory and cannot handle the vast input arrays inherent in satellite imagery. To circumvent these deficiencies, the next step was to implement the best training algorithm in C under UNIX (a virtual memory operating

system) so that two-dimensional grid values analogous to pixel values can be used as input. The increase in the number of input nodes requires an increase in the number of hidden nodes. We emulated pixel input with a 50 x 50-point grid, giving 2,500 input nodes-- an increase by a factor of almost 10 over the previous case.

At this point it was necessary to train this new grid-input network, rewrite the Gulf Stream profiles into this grid-type format, and test the grid-input network for convergence. As before, we modified parameters of the learning algorithm, number of nodes, and scaling of input and output values empirically at this stage in order to achieve convergence. Finally, we trained this network with only 77 of the available 86 GOAP product Gulf Streams, leaving a randomly-selected 9 as a test set.

When convergence is achieved, it is appropriate to run the fully trained network on any of the 9 test Gulf Streams. The coefficients produced by the network are then compared to the actual coefficients to determine whether they are well-correlated.

We then planned to test the performance of the network with an IR edge image projected onto the input grid. If the performance of the network is degraded, it would then be necessary to define a new training set made up of simulated noisy edges. Such a set could be constructed, e. g., from GOAP mesoscale products with random sections of random length missing. and with random segments of noise added. The statistics of this random noise may have to be matched carefully to the statistics of SST front noise observed in the six composite images.

Finally, we expected to quantify the performance of the network with statistical measures such as mean and rms difference between network and mesoscale product Gulf Streams, and significance level for the differences.

We used Neuralworks software and several Intel 80386-based microcomputers (386 PC). Neuralworks operates under DOS but is limited in memory, so the 50 x 50 latitude-longitude grid had to be implemented in the virtual-memory environment of UNIX on the 386 machines. Imagery is displayed on EGA graphics monitors and hardcopies made on a Laserwriter for which PostScript code had to be written.

5. RESULTS ACHIEVED

The coefficients generated with the Neuralworks network are in excellent agreement with the actual coefficents in the training set. This leads us to conclude that a neural network can produce meaningful coefficients for CEOF modes; thus, a neural network can generate a continuous Gulf Stream.

We can quantify this agreement by computing for each coefficient a mean and a variance over the ensemble of 86 Gulf Streams; these are listed in Table 1. Table 1 shows that the means of the Neuralworks network typically agree with the actual mean within 3.6%. But more importantly, the 264-10-6 network (the significance of this name will be clear shortly) also mimics the variance in Gulf Stream coefficients--typically hitting the variance within 11.8% also. The correlation coefficient for the six sets of CEOF mode coefficients is typically greater than 0.98.

Table 1. Mean and Variance of 86 Gulf Streams for 1st 3 Modes, 264-10-6 Network

Mode Coefficient	Actual Mean	Actual Variance	264-10-6 Mean	264-10-6 Variance	RMS Difference Between Network and Actual
1, real	0.36686	0.01994	0.32810	0.01669	0.00236
1, imag.	0.51797	0.00703	0.54308	0.00362	0.00526
2, real	0.62294	0.02015	0.61439	0.02122	0.00041
2, imag.	0.52452	0.00795	0.53376	0.00809	0.00019
3, real	0.50531	0.00785	0.50749	0.00761	0.00009
3, imag.	0.49391	0.00653	0.50644	0.00650	0.00025

This good agreement is obtained with the following network parameters selected through experiment. The learning algorithm is back propagation;[11] convergence is achieved with 100,000 iterations through the training set with the learning coefficient set to 0.9 and the momentum coefficient set to 0.6. The number of hidden layers is 1; the number of nodes on that layer is 10 (hence the network consists of 264-10-6 input-hidden-output nodes, respectively). The coefficients placed or retrieved at the six output nodes must be separately scaled to range between the values of 0.2 and 0.8 in order for the higher mode coefficients to converge closely.

We successfully implemented a new network in the C programming language that would operate on input nodes arranged as a 50 x 50 grid. The Mercator projection region between 34°N and 45°N latitude, and 75°W and 50°W longitude, is mapped onto this 50 x 50 grid. The grid's nominal resolution is 50 km. The 86 GOAP mesoscale product Gulf Streams are mapped onto this grid and used as input to the new neural network. We call the new network the grid-input network, or the 2500-40-6 network, to distinguish it from the earlier network. This network contains 40 nodes in one hidden layer, learns using back propagation, and uses the same scaling for the conversion between output nodes and CEOF coefficients as before. This network is trained with 77 of the 86 Gulf Streams; 9 Gulf Streams selected at random were held back for testing. It converged on its final form after 150,000 passes through the training set. This convergence took about 7 days of run time on our 25 MHz machine.

Table 2. Mean and Variance of 77 Gulf Streams for 1st 3 Modes, 2500-40-6 Network

Mode Coefficient	Actual Mean	Actual Variance	2500-40-6 Mean	2500-40-6 Variance	RMS Difference Between Network and Actual
1, real	0.37633	0.01889	[illegible]	[illegible]	[illegible]
1, imag.	0.51734	0.00696	0.51604	[illegible]	[illegible]
2, real	0.61178	0.01922	0.61864	[illegible]	[illegible]
2, imag.	0.52384	0.00671	0.52465	[illegible]	[illegible]
3, real	0.50207	0.00707	0.50414	0.00791	0.00113
3, imag.	0.49444	0.00445	0.49694	0.00596	0.00156

Table 2 shows that the means of the grid-input network typically agree with the actual

mean within 0.7% for the training set. Again, more importantly, the 2500-40-6 network also matches the variance in Gulf Stream coefficients, typically coming within 13.0% of the correct variance. The correlation coefficient for the 6 sets of CEOF mode coefficients is greater than 0.87. This is extremely encouraging because these good measures are achieved without optimizing the network's parameters. Of further importance is that the processing by the network is extremely fast; it takes less than 1 second to produce three complex mode coefficients from 50 x 50 gridded input.

Table 3. Mean and Variance of 9 Test Gulf Streams for 1st 3 Modes, 2500-40-6 Network

Mode Coefficient	Actual Mean	Actual Variance	2500-40-6 Mean	2500-40-6 Variance	RMS Difference Between Network and Actual
1, real	0.32451	0.01083	0.37834	0.02275	0.02468
1, imag.	0.53443	0.00471	0.52649	0.00726	0.00328
2, real	0.65976	0.01118	0.62632	0.02066	0.01529
2, imag.	0.52343	0.01317	0.50572	0.00451	0.00813
3, real	0.51534	0.007122	0.48515	0.00488	0.00378
3, imag.	0.46795	0.01119	0.48532	0.00370	0.01652

The grid-input network does less well with data in the test set (Figure 2 and Table 3), but still achieves agreement within 6.0% for the means, though only within 68% of the variances. The performance in matching the variance is skewed by poor performance on just two Gulf Stream axes because the test set is so small.

The trained 2500-40-6 network performs moderately well on noisy edge imagery, also. A 512 x 512 edge image is transformed to the much coarser 50 x 50 grid to provide a noisy input data set. In spite of looking nothing like the training set of Gulf Streams, the input does not cause the network to diverge. In fact, the network generates quite reasonable coefficients. The network Gulf Stream is within 60 nmi of the actual Gulf Stream for most of its length, and properly identifies Gulf Stream SST edges by crossing over them. This result is encouraging, but is considered preliminary at this point.

The modest successes achieved for a network not optimized for gridded input and not trained for noisy edges indicate that this neural network is robust, i. e., not unstable over a range of parameters. We expect the network to achieve better performance with further experimentation. The fast processing (less than 1 second) of a 50 x 50 edge image by a previously trained network is a great strength of the method.

6. PLANS FOR NEXT STAGE OF RESEARCH

The next logical step is to extend the range of the study by expanding upon the number of mode coefficients the network produces so that a better, more useful Gulf Stream description emerges from the system. The production of more and better mode coefficients requires increasing the resolution of the grid input to the neural network. This, in turn, requires a greater number of computations, which suggests that special hardware, such as a high-speed digital signal processing chip, would be advantageous.

The IR images in which we wish to locate the Gulf Stream cover a much larger area than

that in which the Gulf Stream has ever been located. The input nodes of the network which cover this area contain no useful information for the network, but do increase the computational burden. This suggests a logical first step for future research. By obtaining the envelope in which the Gulf Stream has been located in the past as defined, e. g., by GOAP mesoscale products, we will be able to eliminate those nodes which correspond to geographical areas through which the Gulf Stream has not been known to pass. We estimate the envelope will cover one-third of the area now represented by the input nodes to the network. Thus this step would allow us to increase the resolution of the input grid by a factor of three without requiring any additional calculations.

The main impediment to increasing the resolution of the input grid further (and thereby enabling more mode coefficients to be produced) is the large number of computations needed to train the neural network. In order to carry out the proposed steps for the effort in a reasonable amount of time additional processing power will be required. As suggested above, a (relatively inexpensive) processing board could increase the speed of network training (by an estimated factor of 50). This addition would also require some software changes, although they would probably be minor.

Once the historical envelope of the Gulf Stream has been determined, the images and Gulf Streams used in the earlier study will need to be regridded to cover the envelope so determined, at a resolution increased by a factor of 3. Then, the previous neural network must be trained on the regridded data. This will enable us to compare the results to that of the previous work in order to establish the effects of increased resolution and the actual speed-up offered by the additional processing power. Next, we will attempt to quantify the effects of the increased resolution on the quality of the network's output.

At that point it will be necessary to decide upon the more fruitful direction for further research. We must decide whether a higher resolution is needed to produce the present number of mode coefficients with sufficient accuracy, or if more mode coefficients could be produced at this resolution. Based on this decision, we will modify the network in one of two ways. If the results indicate that a higher resolution is required, the images which form the training set will be regridded at a higher resolution. If the results indicate more mode coefficients could be produced at the present resolution, then the number of output nodes of the network will be increased.

It is obvious that the cycle of testing, evaluation, and modification could be repeated several times. The objective is to provide a neural network system which can automatically derive a useful mathematical (CEOF) description of the Gulf Stream directly from edge images produced from satellite observations. The criterion for usefulness is that the Gulf Stream description should reproduce that produced by a skilled human analyst from the same data to a precision adequate to meet the requirements of the U. S. Navy. Such a system has the potential to become a useful operational tool.

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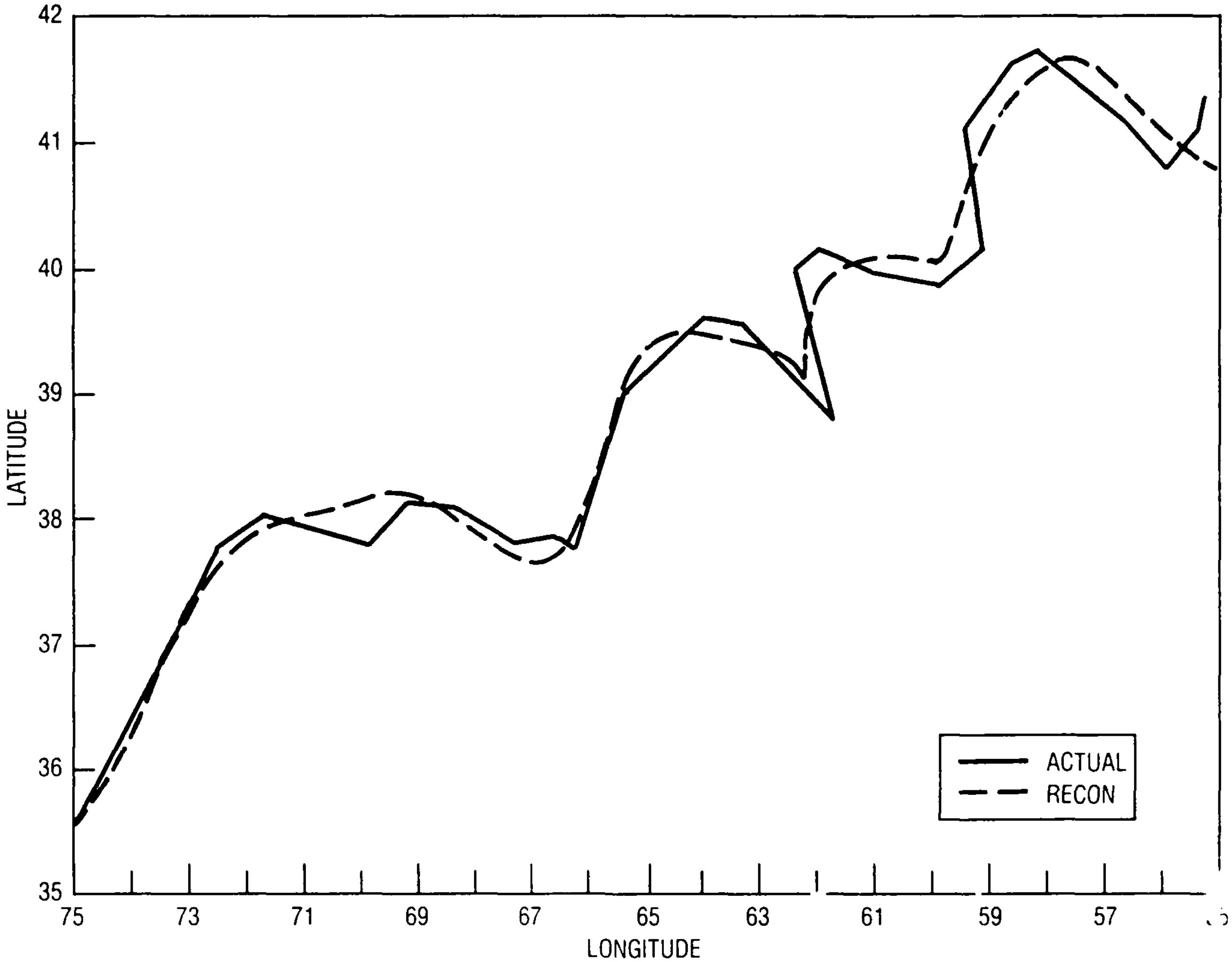

Figure 1. Capacity of 10 Complex Empirical Orthogonal Functions (CEOFs) to reconstruc (dashed line) even a convoluted Gulf Stream produced by an analyst (solid line). The analyst Gulf Stream is from the GOAP mesoscale product for April 18, 1986.

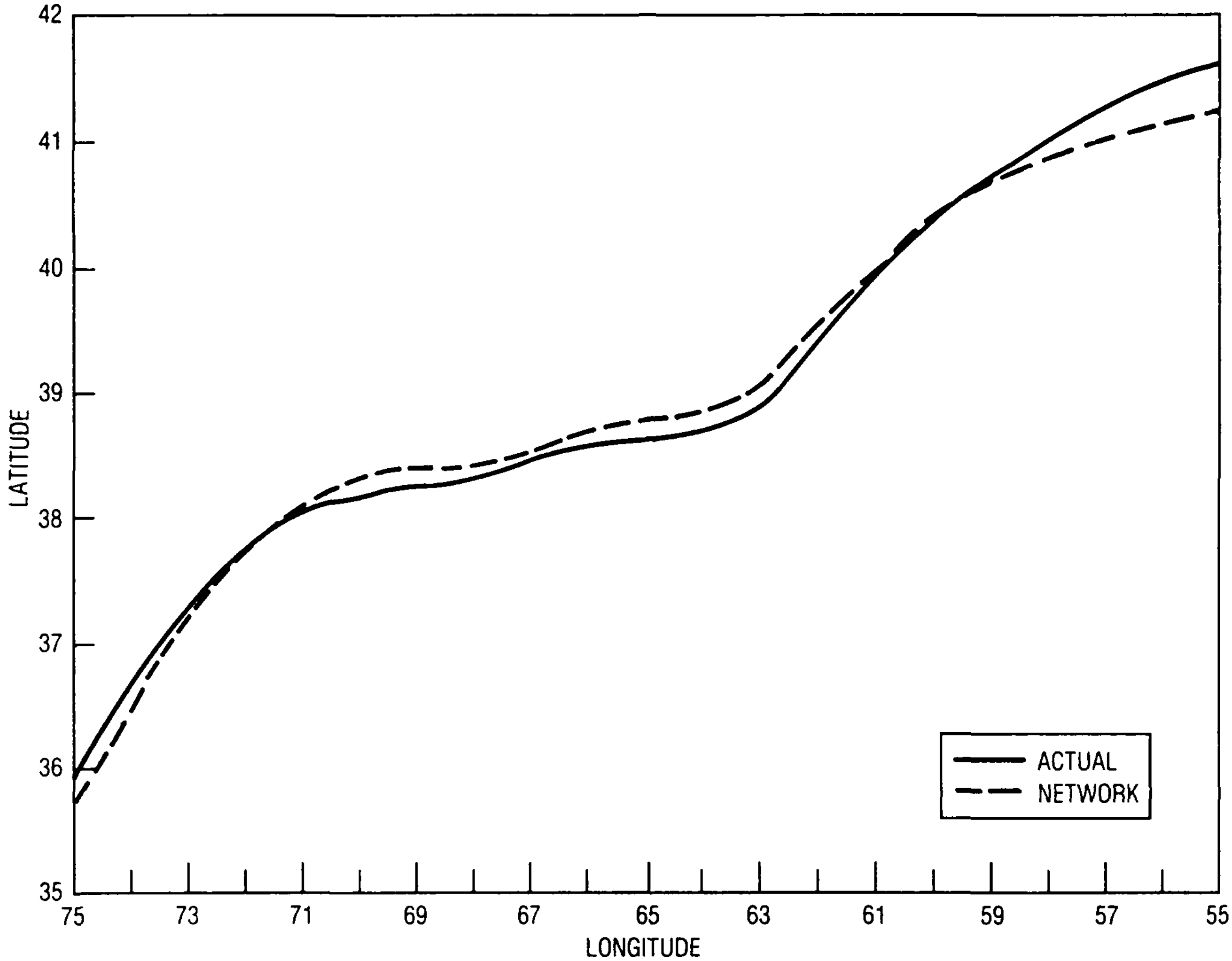

Figure 2. Proximity of 3 modes from grid-input or 2500-40-6 neural network (dashed line) to the actual 3 modes (solid line) for a test Gulf Stream.